

# Working Memory Facilitates Event Segmentation via Boundary-Triggered Reactivation and Partial Accumulation During Events

Berna Güler<sup>1\*</sup>, Sümeyye Karahamza<sup>1\*</sup>, Yağmur D. Şentürk<sup>1</sup>, Oded Bein<sup>2</sup>,  
David Clewett<sup>3</sup>, & Eren Günseli<sup>1</sup>

1. Department of Psychology, Sabancı University, Istanbul, Türkiye
2. Weill Cornell Institute of Geriatric Psychiatry, Department of Psychiatry, Weill Cornell Medicine, New York, New York, 10065, USA.
3. Department of Psychology, University of California, Los Angeles, CA, USA

\* Shared first authorship.

Corresponding author: berna.guler@sabanciuniv.edu

## Abstract

Event segmentation is the cognitive process of dividing continuous experiences into meaningful units. Although working memory (WM) is believed to play an instrumental role in event segmentation, its specific contribution remains under debate. Here, we used two electroencephalography (EEG) indices of WM load, alpha-band suppression and contralateral delay activity (CDA) amplitude, to test whether WM supports event segmentation by gradually accumulating information during unfolding events or by reactivating information at the transitions between events (i.e., event boundaries). Participants viewed object images paired with sounds that both remained in the same category for 6 consecutive items to form a stable event, followed by 2 items from another category, creating an event boundary. Temporal order and sequential memory were used to assess event segmentation. We found increased alpha-band suppression following event transitions, supporting the reactivation account. Evidence for the accumulation was mixed, with no evidence for increased alpha-band suppression and moderate evidence for increased CDA during events. These results indicate that WM contributes to event segmentation primarily through boundary-triggered reactivation, with only limited evidence for within-event accumulation.

*Keywords:* working memory, event segmentation, event boundary, episodic memory, alpha-band suppression

Everyday life unfolds continuously, yet we remember experiences as a sequence of discrete events. Event segmentation refers to the process by which ongoing experience is parsed into meaningful units that structure episodic memory, with meaningful changes in the environment signaling event boundaries and transitions between events (Clewett et al., 2019; Ezzyat & Davachi, 2011; Zacks et al., 2007). According to the Event Segmentation Theory (EST), working memory (WM) supports event segmentation by maintaining representations of the current event and updating those representations at boundaries (Speer et al., 2007; Swallow et al., 2009; Zacks, 2020). Supporting this idea, WM properties, such as capacity, updating, and forgetting rate, are correlated with event segmentation ability (Jafarpour et al., 2022; Leroy et al., 2024, 2025; Shim et al., 2024). However, the specific mechanism by which WM contributes to event segmentation remains unclear.

One possibility is that sequential information gradually accumulates in WM over the course of an event (Güler et al., 2024). Because WM capacity is limited, this accumulation must eventually be reset, with event boundaries serving as cues that clear information from the preceding event and free mental resources for encoding the next (Ongchoco & Scholl, 2019; Radvansky & Zacks, 2017). Accumulation within an event may support predictions about unfolding experiences and strengthen associations among memoranda encountered within a shared context. Supporting this idea, Wu et al. (2023) showed that neural patterns became progressively more similar across successive images within an event, as indexed by increasing similarity between the electroencephalography (EEG) patterns evoked by consecutive images, and this effect weakened at boundaries. This progressive increase in neural pattern similarity may reflect the accumulation of information in WM, because greater similarity can arise when successive time points share overlapping memory content.

Another possibility is that WM facilitates the transfer of information to long-term memory (LTM) during an event, with event boundaries triggering reactivation of information from the prior event in WM, helping to bind them together within events and preserve a sense of continuity across events. Indeed, recent studies suggest that reactivation of information occurs at event boundaries, not within events. For example, EEG activity patterns observed during item encoding were subsequently reinstated at event boundaries, but not before (Sols et al., 2017). Silva et al. (2019) extended this finding using EEG while individuals watched movies, showing that stronger boundary-related reactivation of an event predicted better recall of the narrative. Chang et al. (2021) used fMRI during story reading and observed that reactivation at boundaries supported stronger integration of the preceding and upcoming events, enabling the narrative to be represented as continuous. However, whether this reinstatement reflects the reactivation of LTM representations within WM remains unclear.

The goal of the present EEG study was to directly test these two accounts by combining two well-established neural indices of WM load: contralateral delay activity (CDA) and alpha-band suppression. Participants memorized sequences of animate and inanimate images, with event boundaries created by category switches after either six items (events) or two items (boundaries; (DuBrow & Davachi, 2013, 2014). CDA provides a sustained neural index of WM load that

increases with the number of maintained items and asymptotes near WM capacity, making it well-suited for tracking accumulation over time. Alpha-band suppression similarly tracks WM load for both currently encoded information and information retrieved from LTM (Fukuda et al., 2015; Fukuda & Woodman, 2017; Hakim et al., 2019), making it a valid tool to assess reactivation of LTM information in WM. The accumulation account predicts a gradual increase in alpha-band suppression and CDA amplitude within events. In contrast, the reactivation account predicts greater alpha-band suppression at, particularly following events (6 items) than boundaries (2 items).

## Methods

### Participants

A power analysis was conducted in G\*Power 3.1 to estimate the appropriate sample size. This analysis was based on studies that assessed alpha-band suppression across varying WM loads using EEG (Fukuda et al., 2015; Heinz & Johnson, 2017). Heinz and Johnson (2017) reported a significant increase in alpha-band suppression between two- and four-item conditions ( $d = 0.53$ ), and Fukuda et al. (2015) observed a large WM load effect in alpha-band suppression ( $\eta_p^2 = 0.39$ ). Based on these findings, we assumed  $d_z = 0.55$  for our expected 6 (event) vs 2 (boundary) items contrast. A G\*Power analysis (paired t-test, two-tailed  $\alpha = .05$ , power = .80) indicated  $N = 26$ . We collected data from 32 participants between the ages of 18 and 26 from Sabancı University in exchange for course credit. All participants provided informed consent prior to participating in the study. All participants had normal or corrected-to-normal vision and self-reported no history of neuropsychological disorders. Due to ocular and recording artifacts in the EEG data, the data from 9 subjects were excluded, leaving 23 participants (15 female;  $M = 21.4$ ,  $SD = 1.83$ ) for analyses. The final sample provides approximately 78% power to detect this effect, comparable to prior EEG studies of alpha-band suppression modulation by WM load (Fukuda et al., 2015; Heinz & Johnson, 2017; Hu et al., 2019).

### Ethics Statement and Code Availability

This study was performed according to the Declaration of Helsinki principles, and the ethics approval was granted by the Sabancı University Research Ethics Committee (SUREC). All data processing and analysis code will be available on the first author's OSF page (<https://osf.io/tch3n/>) upon acceptance of this manuscript.

### Stimuli

A set of 1068 images of everyday objects (Google Images; Konkle et al., 2010; Konkle & Caramazza, 2013; Konkle & Oliva, 2012) was resized to an equal number of non-transparent pixels (500 x 500) and was randomly divided into two sets: 540 target and 528 non-target stimuli. Target stimuli were those we instructed participants to attend during the study phase, while non-target stimuli were displayed on the other side of the screen and included to balance the visual distribution due to the lateralized nature of the CDA metric. Both sets were grouped into two categories

(animate and inanimate). Each object was shown twice throughout the experiment, once in the first half of the experiment and once in the second half. The presentation order was otherwise random. There were also 6 different sounds – 3 nature and 3 artificial – presented simultaneously with the object images.

The experiment was programmed in MATLAB (Mathworks) Psychtoolbox (Kleiner et al., 2007). The viewing distance to the screen was approximately 85 cm, and the background color was gray. The location cue was a vertically halved, bicolored circle (.35° x .35°), with one side navy blue and the other orange. The location cue represented where the target stimulus would appear. For each block, either the blue or orange color indicated the stimulus location, and their order was counterbalanced across participants. The target and non-target objects were equidistant from the location cue.

## Procedure

The experiment consisted of 44 blocks. Each block consisted of a study phase, a filler task, and a test phase containing 8 image pairs of memory test (4 within- and 4 across-event pairs) for the temporal order and sequential memory tasks. Participants were allowed to take self-paced breaks between blocks during which they were informed about their temporal memory accuracy at the end of each block. Before the experiment, participants completed a practice round requiring a minimum of 50% accuracy on the temporal order and sequential memory tasks. Participants repeated the practice round until they achieved the required accuracy, which took a maximum of two attempts among participants. The block structure for the experiment is depicted in **Figure 1**. Each block consisted of three phases: encoding, change localization task (filler), and temporal memory tests.

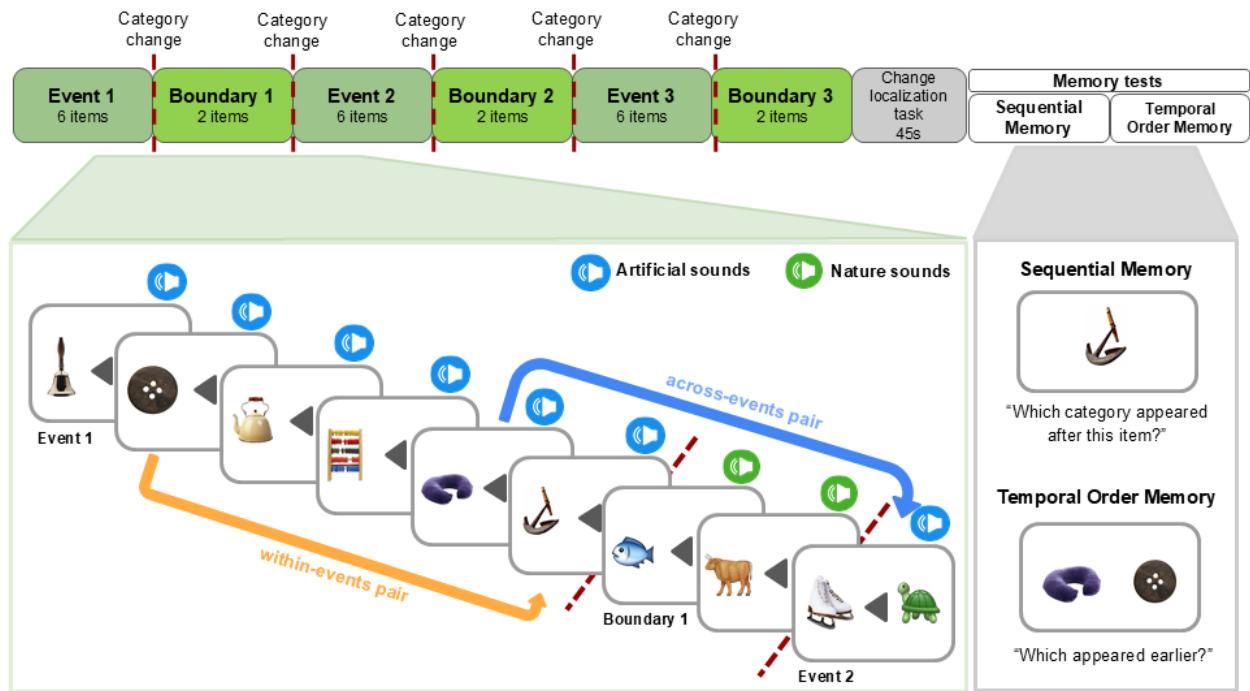
### *Encoding phase*

Each encoding phase started with a location cue presented at the center of the screen for a randomly jittered duration of 1.5-2 seconds. Next, the memory display with two images on each side of the location cue was presented for 2 seconds. Participants were instructed to memorize the target image on the cued side of the screen and ignore the non-cued image. Between each memory display, there was a 1.75-second interstimulus interval (ISI). The first target image was selected to be either animate or inanimate based on the subject, and block numbers were counterbalanced across participants. The following 5 target images were from the same object category. We refer to a series of 6 within-category images as an event. Blocks always started with events.

There was a boundary after each event consisting of two images. We chose to include a two-item boundary for three reasons. First, testing the reactivation account benefits from comparing alpha-band suppression following different event lengths. Second, prior work shows that event segmentation effects are stronger when the context shift persists across more than one item (Güler et al., 2025), making a single-item boundary suboptimal. Finally, limiting the boundary trial to only 2 images helped reduce the likelihood that it would be perceived as its own meaningful event.

The ISI between an event and a boundary was randomly jittered to be between 1.5 and 2 seconds to cancel out any systematic voltage carryover between events and boundaries (Cohen, 2014). The object category varied between events and boundaries. For example, if an event contained animate images, then a boundary contained inanimate images. The animate and inanimate images alternated between being events and boundaries across blocks. Within each block, there were 3 events and 3 boundaries, making up a total of 24 target images.

Each image was accompanied by a category-specific sound with the same onset time (lakeside, jungle, or farm for animate images, and office or traffic for inanimate images). The sound duration matched the duration of the visual presentation of the images. The goal of alternating the category of images and their associated sounds across events and boundaries was to facilitate event segmentation (Heusser et al., 2018; Sols et al., 2017; van de Ven et al., 2021).



**Figure 1. Event sequence for the encoding phase and memory tests.** Participants viewed a series of everyday object images presented laterally. They needed to remember the cued item and ignore the non-cued one. Non-cued item was presented to match the perceptual input – otherwise, the lateral EEG index, the CDA, cannot be reliably attributed to WM (Vogel et al., 2005). The image and sound category alternated every 6 (event) and 2 (boundary) items between animate and inanimate, and artificial and nature sounds, respectively. After the change localization task (filler) of 45 seconds, participants performed sequential and temporal order memory tasks. The sequential memory task probe was either the 5th or 6th image of the event. The temporal order memory probe included pairs of images with always 3 items in between, shown in orange and blue arrows in the flow of objects.

### *Change Localization Task*

Before the memory test phase, participants were asked to perform a change localization task (Zhao et al., 2023). This served two purposes: (1) to measure the participants' WM capacity and (2) to serve as a filler task between encoding and retrieval, minimizing the rehearsal of memory items in WM and any potential recency effects in LTM.

In this task, a black fixation dot ( $0.35^\circ \times 0.35^\circ$ ) at the center of the screen, along with six randomly placed colored squares, was presented on a given memory screen for 2.5 seconds. The probe display was presented after a 1 second blank retention interval. The probe contained the 6 colored squares at their original locations. One of the squares on the probe display had a different color than the memory display. Participants were asked to indicate this different color by clicking on it with the mouse. The probe display remained on screen for 2 seconds regardless of the answer to equate the filler task duration. To account for imperfect mouse clicks, a response area 25% larger than the area of the correct color's square was considered correct. Thus, colored squares were placed at least 1.25 times their size apart from each other. The ITI was 1 second. The change localization task consisted of 12 trials for each block. The filler task started 3 seconds after the end of Phase 1 and took 51 seconds. Therefore, Phase 1 and Phase 3 were 54 seconds apart.

### *Temporal Memory Tests*

Each temporal memory test in a block consisted of a sequential memory test followed by a temporal order memory test. In the sequential memory task, the 5th or 6th images of randomly selected events were presented at the center of the screen. Participants were then asked to indicate the category of the image that appeared immediately after the presented image in the encoding phase. The 5th image of the event constituted the within-event condition because the next object would be the 6th image of the same event. On the other hand, the 6th image of the event constituted the across-events condition, as the next image would belong to the first image of the boundary.

In the temporal order memory test, two images were shown on the screen side by side. One was either the 2nd or the 5th image of a randomly selected event in the encoding phase, and the other was 3 items apart from the first image. For example, the 2nd and 6th images of an event are used for the within-event condition. In the across-events condition, the 5th image of an event was paired with the 1st image of the following, thus crossing the boundary by two items. Participants were then asked to specify which of the images were displayed temporally earlier in the encoding phase.

Both memory tests included 4 probes divided equally per condition (within-events or across-event), with 8 probes in total. The sequential memory test was always first. Participants responded using the right and left arrow keys. In the sequential memory task, the left arrow indicated the animate category and the right arrow indicated the inanimate category. In the temporal order memory task, the left and right arrows were used for the answers corresponding to the images displayed on the left or the right side of the screen, respectively.

## EEG Recordings

The EEG was recorded from 32 sintered - AG/AgCl electrodes positioned at International 10/20 System sites. The electrodes were attached to an elastic cap (actiCAP, Brain Products). The EEG signal was amplified using Brain Products actiCHamp amplifier (actiCHamp Plus, Brain Products GmbH, Gilching, Germany) and was digitized at a 1000 Hz sampling rate.

The vertical EOG (VEOG) was recorded from two external electrodes that were located approximately 2 cm above and below the right eye. Two electrodes (F7 and F8) located approximately 1 cm lateral to the external canthi were used as HEOGs to detect horizontal eye movements. Two electrodes (TP9 and TP10) were attached to the two mastoids. The left mastoid was the online reference. Since the amplification of EEG channels and external EOG channels differs, we applied a scaling factor of 0.1  $\mu$ V (Brain Vision Recorder | User Manual, 2018) to VEOGs to make the magnitude of the VEOG and HEOG recordings compatible with other EEG channels for both online visualization and offline analysis. The EEG data was collected from the following electrodes with a customary layout optimized for collecting data mainly from the parietal and occipital regions: Fp1, Fp2, F3, F4, Fz, FC5, FC6, FC1, FC2, C3, C4, Cz, CP5, CP6, CP1, CP2, P7, P8, P3, P4, Pz, PO7, PO8, PO3, PO4, O1, O2, and Oz. We kept the impedance for the electrodes below 20  $k\Omega$ .

We carried out the EEG analyses using MATLAB R2022b (Mathworks, Natick, MA), the EEGLAB toolbox (version 2021.1; Delorme & Makeig, 2004), the ERPLAB toolbox (version 8.30; Lopez-Calderon & Luck, 2014), and custom scripts. Recording artifacts (muscle noise, slow drifts, saturation, and blocking) and ocular artifacts (eye movements and blinks) were detected manually by visual inspection. Any step-like function in HEOG that exceeded 18  $\mu$ V was rejected as an eye movement. Rejection of the artifacts was performed only before hypothesis testing. Trials containing such artifacts were excluded from the analysis. After artifact rejection, we excluded datasets with less than 80 trials from the analysis.

The data was filtered by an IIR Butterworth filter with a band-pass of .01-40 Hz using the pop\_basicfilter.m function of ERPLAB. The data was then re-referenced offline to the average of the right and left mastoids. The noisy channels were interpolated using the pop\_interp.m function of EEGLAB. Each of the 6 events in each block was epoched using the pop\_epoch.m function of EEGLAB. For events, one epoch consisted of 6 consecutive memory displays, and for boundaries, one epoch consisted of 2 memory displays (corresponding to -2.5 to 22.75 sec for events and -2.5 to 7.75 sec for boundaries relative to the first display onset). Considering the long duration of these epochs, a baseline period of 0.5 seconds prior to the stimulus onset was included in the ERP analyses.

### *CDA analysis*

The CDA was measured at P7/8, PO7/8, and O1/2 as the mean voltage difference at electrodes contralateral versus ipsilateral to the location of each target image from 0.4 seconds to 1 second after the onset of each memory display (Günseli et al., 2019; Ikkai et al., 2010; Vogel et al., 2005; Vogel & Machizawa, 2004). We first compared the CDA amplitude of both events and

boundaries against 0 with a one-sample t-test to determine whether there was a significant CDA. To test the accumulation hypothesis, we then examined a linear trend in CDA amplitude from the 2nd to the 6th images of events. This was done using a linear contrast across image positions 2, 3, 4, 5, and 6 within a repeated-measures ANOVA (with CDA amplitude as the dependent variable, and item position as the independent variable). A significant linear trend in CDA amplitude across 5 consecutive items during encoding could reflect the accumulation of information in WM. We started with the 2nd item, rather than the 1st, because any reactivation of content from the previous event – if it occurs – would likely take place at the 1st item, which serves as the boundary item. Additionally, we compared the CDA amplitude at the 2nd and 6th items using a paired-samples t-test to assess differences between loads. Accordingly, accumulation predicts a larger CDA for the 6th vs the 2nd item, as the accumulated information in WM would be 6 vs 2.

#### *Alpha-band suppression analysis*

To compute alpha-band suppression (8-12 Hz), we created a sinusoid ( $ei2ft$ ) for each frequency and then converted it to Morlet wavelets by tapering it with a Gaussian ( $e^{-t^2/2s^2}$ ; where  $t$  is time and  $s$  is the Gaussian width). The beginning and the end of the data were padded with zeros. All epoched data were restructured into a single continuous EEG data, and then the Fast Fourier Transform (FFT) was applied to both the EEG and Morlet waves. For each frequency, we calculated the dot product of the Fourier-transformed EEG data and Morlet wavelet, then applied inverse FFT to each dot product. We calculated the alpha-band power by averaging power across 8 and 12 Hz, sampled logarithmically. We performed baseline normalization log-transforming the ratio of the power in each frequency in each trial relative to the average baseline (0.5-0.2 seconds before the target onset) of all trials. The log transformation helps compress the scale of the data and makes it easier to interpret differences in power levels across conditions. We averaged alpha-band suppression between 0.4 and 1 seconds after each memory display onset at P7/8, PO7/8, and O1/2, just as done for the CDA. For one participant, the boundary time–frequency analysis required artifact rejection in the long-epoch data because there was a mismatch between the short and long epoch numbers caused by two battery interruptions.

To test our hypotheses regarding the accumulation account, we first examined a linear trend in alpha-band suppression across the 2nd and 6th items, then compared these items using a paired-samples t-test, as for the CDA. To assess the reactivation account, we compared the alpha-band suppression for the 1st item of events and the 1st item of boundaries using a paired samples t-test. If the items from the previous event are reactivated at the boundary, WM load should be higher at the end of an event (6 items) compared to the boundary (2 items), resulting in a larger alpha-band suppression following events compared to boundaries. On the other hand, if there is no reactivation, alpha-band suppression should be equal between events and boundaries, given that the memory load is the same as one item. In addition to these comparisons, we also examined CDA amplitude and alpha-band suppression at boundaries (i.e., 1st and 2nd items).

### *Behavioral analysis*

Sequential memory and temporal order memory tasks were used as behavioral indices of event segmentation (Buonomano et al., 2023). We predicted that temporal order memory accuracy would be higher in the within-event condition compared to the across-event condition, consistent with operationalizations of event segmentation in memory.

We used a change localization task, which measures WM capacity, both as a filler task and to correlate it with accumulation, as we hypothesized accumulation may be limited by individuals' WM capacity. To quantify individual differences in WM capacity, we extracted a WM capacity estimate (K) score for each participant using a formula that was developed by Zhao et al. (2023) and was as follows:  $K = \text{Acc}(\text{change localization}) * N^2 - N / N - 1$ , where  $\text{Acc}(\text{change localization})$  was the change localization task accuracy rate, and  $N$  was the set size, which was 6 for each participant. A higher K score would indicate greater WM capacity.

To complement the frequentist analysis, we also conducted Bayesian analyses to quantify the strength of evidence for both the null ( $H_0$ ) and alternative ( $H_1$ ) hypotheses. This approach was chosen because we did not make directional predictions about whether WM would support segmentation via accumulation within events or via reactivation at boundaries. Bayes factors were interpreted as  $BF_{10} < 1$  = evidence for  $H_0$ , 1-3 = anecdotal evidence for  $H_1$ , 3-10 = moderate evidence for  $H_1$ ,  $> 10$  = strong evidence for  $H_1$  (Schönbrodt & Wagenmakers, 2018).

## Results

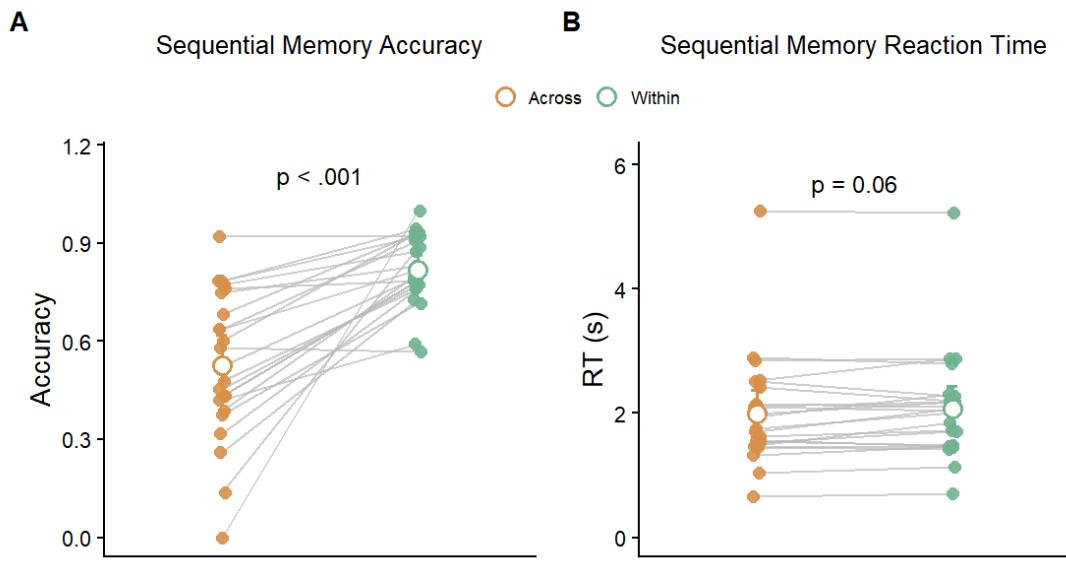
The normality of the difference scores between within- and across-event conditions for temporal order and sequential memory tests was assessed using the Shapiro–Wilk test. For accuracy, temporal order met the normality assumption ( $W = .96$ ,  $p = .66$ ), whereas sequential memory did not ( $W = .88$ ,  $p = .01$ ). For response times, both contrasts satisfied the normality assumption (sequential memory:  $W = .93$ ,  $p = .17$ ; temporal order:  $W = .94$ ,  $p = .21$ ).

### **Behavioral Results**

Sequential memory accuracy was significantly higher for within-event pairs ( $M = 0.82$ ,  $SD = 0.11$ ) than across-event pairs ( $M = 0.53$ ,  $SD = 0.23$ ),  $t(22) = -5.99$ ,  $p < .001$ ,  $d = 1.25$ , 95% CI:  $-2.02$ ,  $-0.97$ ], with strong evidence supporting this effect ( $BF_{10} = 41$ ). Response times for the sequential memory were slower for within-events ( $M = 2.07$ ,  $SD = 0.87$ ) than across-events ( $M = 2.00$ ,  $SD = 0.89$ ), though this difference was weakly supported ( $t(22) = -1.95$ ,  $p = .06$ ,  $d = -0.41$ , 95% CI  $[-0.88, -0.01]$ ,  $BF_{10} = 1.09$ ) (see **Figure 2**). This pattern suggests event segmentation during encoding.

Accuracy in the temporal order memory did not differ between the within- ( $M = 0.49$ ,  $SD = 0.06$ ) and across- ( $M = 0.49$ ,  $SD = 0.05$ ) events conditions,  $t(22) = -0.02$ ,  $p = 0.97$ ,  $d = 0.006$ , 95% CI  $[-0.03, 0.03]$ ,  $BF_{10} = 0.21$ . Response times for within-event ( $M = 2.52$ ,  $SD = 0.68$ ) and across-event ( $M = 2.54$ ,  $SD = 0.73$ ) conditions showed no significant difference,  $t(22) = 0.48$ ,  $p = .63$ ,  $d = -0.10$ , 95% CI  $[-0.11, 0.06]$ ,  $BF_{10} = 0.24$ .

Individuals' WM capacity was assessed with K score with an average score of 1.46 ( $SD = 0.80$ , 95% CI = [1.13 1.79]) which was considerably low compared to the average K score of 2.45 in Zhao et al. (2023). To assess whether WM capacity was related to sequential memory performance, we examined Spearman rho ( $\rho$ ) correlations between K scores and sequential memory measures. K score was not correlated with sequential memory accuracy (within-event:  $\rho(21) = .13$ ,  $p = .56$ ; across-event:  $\rho(21) = .06$ ,  $p = .79$ ) or with the sequential memory segmentation score (across-within difference:  $\rho(21) = -.08$ ,  $p = .72$ ). All remaining correlations were also non-significant ( $\rho \leq .32$ ,  $p \geq .13$ ).



**Figure 2.** Sequential memory accuracy (A) and response time (B) for across and within-events.

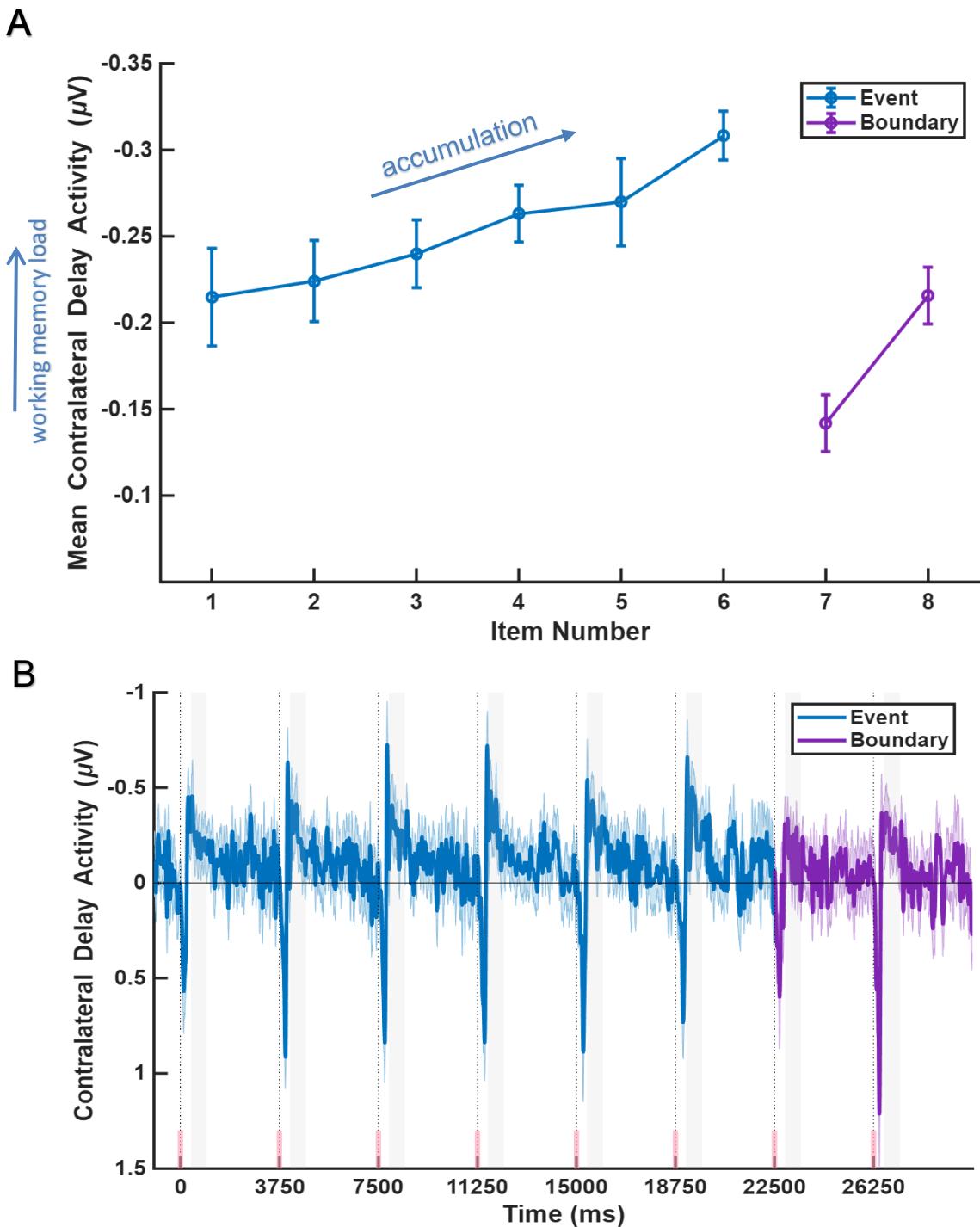
## EEG Results

*A linear trend in CDA moderately supports the accumulation of information in WM during events*

To establish that CDA reliably indexed WM engagement in our sample, we first tested whether mean CDA amplitude differed from zero. CDA was significantly below zero,  $t(22) = -4.19$ ,  $p < .001$ ,  $d = -0.87$ , 95% CI [-1.35, -0.38],  $BF_{10} = 82.4$ . Critically, CDA amplitude increased as a function of item position within events. A linear trend analysis revealed a significant increase in CDA amplitude from the 2nd to the 6th item, consistent with gradual accumulation of information in WM (linear trend within repeated-measures ANOVA:  $t(22) = -2.50$ ,  $p = .02$ ,  $d = -0.19$  (see **Figure 3A**). However, the repeated-measures ANOVA did not provide strong evidence for a main effect of item order,  $F(4, 88) = 2.17$ ,  $p = 0.07$ ,  $\eta^2 = 0.09$  ( $BF_{10} = 0.60$ ), suggesting a continuous rather than stepwise change in CDA across the event. Consistent with the linear trend, a direct comparison between early and late event positions showed that CDA amplitude was significantly larger for the 6th item ( $M = -0.30$ ,  $SD = 0.33$ ) than for the 2nd item ( $M = -0.22$ ,  $SD = 0.32$ ),  $t(22) = 2.76$ ,  $p = .01$ ,  $d = 0.57$ , 95% CI [0.12, 1.01], ( $BF_{10} = 4.40$ ). At event boundaries, CDA also increased from the 1st item ( $M = -0.14$ ,  $SD = 0.28$ ) to the 2nd item ( $M = -0.21$ ,  $SD = 0.28$ ),  $t(22) = 2.17$ ,  $p = .03$ ,  $d = 0.47$ , 95% CI [0.02, 1.01], ( $BF_{10} = 3.40$ ).

$0.34$ ,  $t(22) = 2.23$ ,  $p = .03$ ,  $d = 0.46$ , 95% CI [0.03, 0.89]). However, the Bayesian Factor was smaller than 3, suggesting weak evidence ( $BF_{10} = 1.71$ ).

We next applied the same analyses to bilateral alpha-band suppression to track the accumulation of information across items within events. In contrast to the CDA results, alpha-band suppression did not exhibit a systematic linear change from the 2nd to the 6th item of events,  $t(22) = 0.34$ ,  $p = 0.73$ ,  $d = .07$ , 95% CI [-0.10, 0.17]. Consistent with this pattern, a repeated-measures ANOVA provided strong Bayesian evidence in favor of the null hypothesis of no linear modulation in alpha-band suppression across items ( $BF_{10} = 0.07$ ),  $F(4, 88) = 0.66$ ,  $p = .61$ ,  $\eta^2 = .02$ . Thus, unlike CDA, alpha-band activity did not systematically vary as a function of item order within events. Direct pairwise comparisons further supported this conclusion. Alpha-band suppression did not differ significantly between the 2nd and 6th items of events,  $t(22) = 0.07$ ,  $p = .94$ ,  $d = 0.01$ , 95% CI [-0.39, 0.42],  $BF_{10} = 0.21$ . However, the 1st item of the boundaries ( $M = -3.02$ ,  $SD = 0.38$ ) indicated higher alpha-band suppression compared to the 2nd item ( $M = -2.72$ ,  $SD = 2.41$ ) at event boundaries,  $t(22) = -2.12$ ,  $p = .04$ ,  $d = -0.44$ , 95% CI [-0.86, 0.01],  $BF_{10} = 1.43$ . Thus, there was no evidence for the accumulation of event items in alpha-band suppression. However, there was a higher alpha suppression of the 1st boundary item compared to the 2nd item. Overall, we obtained mixed evidence for the accumulation of information in WM.

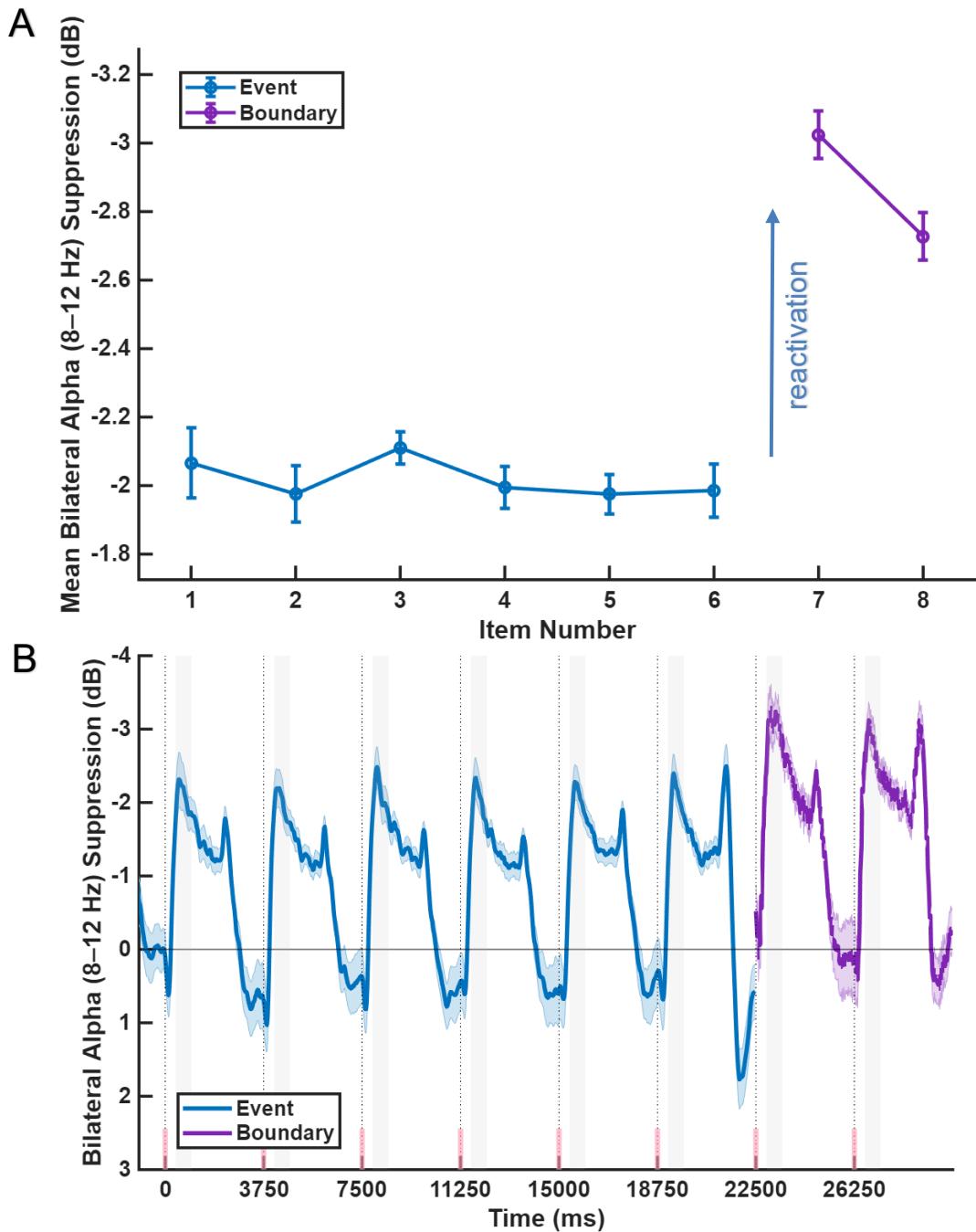


**Figure 3.** The contralateral delay activity (CDA), a marker of working memory load, gradually increased across a stable event, providing evidence of item accumulation effect in working memory. (A) The mean CDA amplitude of each item in an event (6 item positions) versus boundaries (2 item positions), depicted in a line plot. (B) the CDA amplitude over time within main, or contextually stable, events. Pink bars represent the onset of the item pairs during encoding. The CDA time frames used in the analyses are depicted in light gray. Note: Error bars are 95% confidence intervals.

*Larger alpha-band suppression following boundaries supports WM reactivation of event items*

The average alpha-band suppression across items is shown in **Figure 4A**. The reactivation account and event segmentation predict larger alpha-band suppression following events compared to boundaries, as the content of reactivation would involve 6 versus 2 items, respectively. To test this, we compared alpha-band suppression at the 1st item of boundaries (i.e., the first item following a transition) and the 1st item of events (i.e., the first item following a transition). There was strong evidence for a larger (more negative) alpha-band suppression;  $t(22) = 4.22, p < .001, d = 0.88, 95\% \text{ CI } [0.39, 1.35], \text{BF}_{10} = 89.38$ , following boundaries ( $M = -3.42, SD = 2.40$ ) compared to events ( $M = -2.56, SD = 1.81$ ), providing support for the WM reactivation account.

To directly contrast the accumulation and reactivation accounts, we compared the alpha-band suppression between the 6th item of events and the 1st item of boundaries. Under the accumulation account, WM load should increase across the six items of an event, such that the 6th item reflects a load of approximately six items (or capacity), whereas the 1st item of boundaries should reflect a reset load of one item. Under the reactivation account, items are not gradually maintained in WM during the event; instead, they are reactivated only when encountered with a boundary. Thus, the 6th item should reflect a load of one item (the current item), while the 1st item of the boundary should reflect a higher load due to reactivation of the preceding six event items. There was anecdotal support for a larger alpha-band suppression at the boundaries' 1st item ( $M = -3.42, SD = 2.40$ ) than at the events' 6th item ( $M = -2.74, SD = 2.05$ ), providing support for the reactivation account;  $t(22) = 2.08, p = .04, d = 0.43, 95\% \text{ CI } [0.003, 0.89], \text{BF}_{10} = 1.35$ .



**Figure 4.** Alpha-band suppression results support the idea that items from a stable event are reactivated at event boundaries. (A) Bilateral alpha-band suppression across event and boundary items, depicted in a line graph. (B) Bilateral alpha-band suppression during both events and boundaries over time. Pink bars represent the image onsets, respectively. The time frames for the bilateral alpha-band suppression calculation used in our analyses are depicted in light grey. The error bars represent the standard error of the mean for data corrected for between-subjects variance.

### *Correlational analysis for neural WM indices*

Thus far, we have identified strong evidence for reactivation of information at boundaries and mixed evidence for accumulation of information in WM during event encoding. Next, we examined whether our EEG measure of WM accumulation across an event was related to individual differences in WM capacity. To investigate this, we examined individual differences in the Spearman correlation between increases in individual CDA, as a measure of information accumulation, and their WM capacity (K), which was insignificant ( $\rho (21) = .17, p = .43$ ). Consistently, Spearman correlational analysis indicated that bilateral alpha-band suppression difference between the first items of boundary ( $\rho (21) = .03, p = .86$ ) and first item of the events ( $\rho (21) = -.09, p = .68$ ) was not significantly correlated with WM capacity. Together, these null correlations suggest that individual differences in WM capacity do not strongly constrain the degree of neural accumulation or boundary-related reactivation observed in the present task.

## Discussion

Working memory (WM) has long been implicated as a key component of event segmentation (Kurby & Zacks, 2008; Zacks et al., 2007), yet how WM specifically contributes to this fundamental cognitive process is unknown. Here, we investigated two accounts: the accumulation account proposes that information gradually accumulates in WM over the course of an event and is flushed at an event boundary. Accumulation should be reflected in a gradual increase in EEG indices of WM load within a stable event, followed by a rapid decrease at the following boundary. In contrast, the reactivation account suggests that information encountered during an event is not continuously maintained in WM but rather is reactivated when a boundary occurs. This account predicts higher WM load indices at event boundaries, scaling with the amount of the content of the reactivated event. Our EEG results provided strong support for the reactivation account and only moderate support for the accumulation account.

Consistent with the reactivation account, alpha-band suppression was higher at the boundary following 6-item events compared to 2-item boundaries. Because only one item was presented as the 1st item both in boundaries and events, this effect cannot reflect active maintenance of the *current* item (Fukuda et al., 2015; Fukuda & Woodman, 2017). Rather, it suggests that item representations from the *preceding* event were reactivated in WM at boundaries, increasing WM load in proportion to event length. Since this reactivation evidence is based on a load-sensitive EEG index, it is consistent with the concurrent reinstatement of multiple items from the concluding event. This extends prior evidence for boundary-triggered reactivation (Silva et al., 2019; Sols et al., 2017), which relied on multivariate pattern similarity and therefore could not distinguish between serial replay and simultaneous reactivation of multiple event items.

We observed mixed evidence for the accumulation of within-event memoranda in WM. A linear increase across items was present in the CDA but not in alpha-band suppression. Likewise, comparing the 2nd and 6th items of events yielded moderate evidence for a CDA difference but not in alpha-band suppression. Explaining this discrepancy is not straightforward. One possibility is capacity-limited accumulation in WM, whereby information is accumulated during an event but up to the WM capacity of ~3 items (cf. Luck & Vogel, 1997; Vogel & Machizawa, 2004). This

constraint may operate either through replacement of earlier items once capacity is reached or through representational compression, whereby multiple items are integrated into a smaller number of chunks (Güler et al., 2024). In both cases, effective WM load may remain relatively stable despite ongoing encoding. A second possibility is that alpha-band suppression reflects both boundary-triggered reactivation of prior event information (Fukuda & Woodman, 2017) and the encoding of newly presented items (Fukuda et al., 2015). Under this account, alpha-band suppression would be high in early in an epoch due to reactivation and remain relatively stable across subsequent within-event items. In contrast, the CDA primarily reflects newly encoded items and is insensitive to the reinstatement of previously encoded information (Adam et al., 2018), leaving more room to increase over the event.

What function could reactivation serve? Reactivation at boundaries could facilitate the formation of associations both within and across events. By concurrently reinstating event items, reactivation can strengthen their associations via mnemonic binding with prior event representations (Baldassano et al., 2017; Ben-Yakov & Henson, 2018; DuBrow & Davachi, 2016). Moreover, reactivating the previous event may help associate the prior experiences with the new one, thereby establishing a subjective sense of continuity (Clewett et al., 2019; Hahamy et al., 2023; Schlichting & Preston, 2016; Sols et al., 2017).

Alongside observing strong evidence for reactivation, we observed moderate and mixed evidence of accumulation in WM, suggesting that these processes are not mutually exclusive but may operate at different moments and levels of representation. Reactivation may occur at event boundaries, reinstating prior event information into an active state, whereas accumulation may unfold within events as newly encoded items are incorporated into WM. Under this account, event segmentation is supported by a dynamic interplay between reactivation and accumulation, such that prior event representations are reactivated to provide a sense of continuity, while new information is progressively accumulated and integrated as the event unfolds.

If previous event items are reactivated in WM at a boundary, why have behavioral studies shown that accessing information from a previous event is harder than the current event? For example, Radvansky et al. (2011) found that crossing a doorway, identified as an event boundary, decreased memory performance and led to slower response times for objects encountered before the transition. This finding suggests that former WM contents are flushed at event boundaries. Similar results were observed in studies using real rooms, video manipulations, or movement, indicating that information in WM is flushed when encountering an event boundary (Baker & Levin, 2015; Lawrence & Peterson, 2016; Ongchoco & Scholl, 2019; Pettijohn & Radvansky, 2016; Radvansky et al., 2010; Radvansky & Copeland, 2006).

We propose two alternative explanations to reconcile the findings of the current study, whereby the previous event was reactivated, and the studies that claim the previous event is flushed (for a review, see Güler et al., 2024). The first involves perceptual interference: context changes, such as different room colors and furniture shapes, can distort memory strength (Clapp et al., 2010; Dolcos et al., 2007; Hakim et al., 2019; Rademaker et al., 2015; van Moorselaar et al., 2015). This interference can cause a decline in memory accessibility, reflecting degraded WM representations

rather than their removal from WM. The second explanation involves attentional blinks or lapses that occur at event boundaries. Attending to an event boundary might cause individuals to miss other information because boundary detection captures attentional resources, leading to a temporary decrease in perceptual processing—similar to an attentional blink. During this brief attentional lapse, incoming information is less likely to be encoded into WM, resulting in forgetting of items that occur immediately around the boundary (Allen et al., 2004; Kumar et al., 2016; McArthur et al., 1999; Tombu & Seiffert, 2008), which may underlie the underestimation observed in Ongchoco & Scholl (2019). From this perspective, reactivation and attentional disruption can co-occur: prior event items may be reactivated at boundaries but become temporarily inaccessible when boundary processing consumes attentional resources. Future research is needed to dissociate the contributions of flushing, attentional lapses, and the difficulty of accessing the memory of the previous event.

Our findings are consistent with prior neuroimaging studies testing the role of WM in event segmentation. However, existing neural evidence does not fully specify the mechanisms involved in this process, as signals attributed to WM could also reflect other memory-relevant processes engaged during continuous experience. While multivariate pattern similarity for event items can be considered an index of WM reactivation, it may also reflect other memory-relevant processes, such as offline replay (Liu et al., 2019) or narrative integration that maintains coherence across events (Chang et al., 2021). Likewise, increasing pattern similarity within events (Wu et al., 2023) could reflect the progressive accumulation of sequential information in WM. Still, it could also arise from the contextual stabilization of the event through two distinct mechanisms that do not require constant WM storage. First, stabilizing context representation can increase pattern similarity across consecutive items (Baldassano et al., 2017), as items are not represented in isolation but rather in context. Second, as individuals form a more stable understanding of the event context, their predictions about upcoming items become increasingly precise. Thus, neural activity during each item reflects both the item itself and the prediction of the next one. As these predictions become more accurate, they more closely match what actually appears next. Consequently, the neural activity evoked by one item becomes more similar to the activity evoked by the following item (De Gardelle et al., 2013; Egner et al., 2010; Summerfield & De Lange, 2014; Walsh et al., 2020). Therefore, both increased prediction precision and contextual convergence can produce greater pattern similarity within an event, even in the absence of WM accumulation. To provide direct evidence to distinguish accumulation and reactivation of event items in WM, the present study has used load-sensitive electrophysiological markers.

In conclusion, by using temporally precise electrophysiological indices of WM load, we found two key results. First, individuals reactivated item representations from the preceding event at boundaries. Second, they showed only modest accumulation of information in WM during events. These findings suggest that stronger within-event associations across memoranda may result from the reactivation of prior event representations at event boundaries. By dissociating neural signatures of accumulation and reactivation, this study provides a mechanistic perspective on how WM may contribute to the organization of distinct events in perception and memory.

### Acknowledgments

This study was funded by Sabancı University Integration Projects Fund awarded to Eren Günseli (grant #: B.A.CG-21-02288). We thank İlayda Efsane Algin, Sinem Subaşı, İlaha Mammadova, Bahire Büşra Temur for their contributions in data collection and İdil Tatar for her contributions in literature review.

### References

Adam, K. C. S., Robison, M. K., & Vogel, E. K. (2018). Contralateral Delay Activity Tracks Fluctuations in Working Memory Performance. *Journal of Cognitive Neuroscience*, 30(9), 1229–1240. [https://doi.org/10.1162/jocn\\_a\\_01233](https://doi.org/10.1162/jocn_a_01233)

Allen, R., Mcgeorge, P., Pearson, D., & Milne, A. B. (2004). Attention and expertise in multiple target tracking. *Applied Cognitive Psychology*, 18(3), 337–347. <https://doi.org/10.1002/acp.975>

Baker, L. J., & Levin, D. T. (2015). The role of relational triggers in event perception. *Cognition*, 136, 14–29. <https://doi.org/10.1016/j.cognition.2014.11.030>

Baldassano, C., Chen, J., Zadbood, A., Pillow, J. W., Hasson, U., & Norman, K. A. (2017). Discovering Event Structure in Continuous Narrative Perception and Memory. *Neuron*, 95(3), 709-721.e5. <https://doi.org/10.1016/j.neuron.2017.06.041>

Ben-Yakov, A., & Henson, R. N. (Eds.). (2018). The Hippocampal Film Editor: Sensitivity and Specificity to Event Boundaries in Continuous Experience. *Journal of Neuroscience*, 38(47), 10057–10068. <https://doi.org/10.1523/JNEUROSCI.0524-18.2018>

Buonomano, D. V., Buzsáki, G., Davachi, L., & Nobre, A. C. (2023). Time for Memories. *The Journal of Neuroscience*, 43(45), 7565–7574. <https://doi.org/10.1523/JNEUROSCI.1430-23.2023>

Chang, C. H. C., Lazaridi, C., Yeshurun, Y., Norman, K. A., & Hasson, U. (2021). Relating the Past with the Present: Information Integration and Segregation during Ongoing Narrative Processing. *Journal of Cognitive Neuroscience*, 33(6), 1106–1128. [https://doi.org/10.1162/jocn\\_a\\_01707](https://doi.org/10.1162/jocn_a_01707)

Clapp, W. C., Rubens, M. T., & Gazzaley, A. (2010). Mechanisms of Working Memory Disruption by External Interference. *Cerebral Cortex*, 20(4), 859–872. <https://doi.org/10.1093/cercor/bhp150>

Clewett, D., DuBrow, S., & Davachi, L. (2019). Transcending time in the brain: How event memories are constructed from experience. *Hippocampus*, 29(3), 162–183. <https://doi.org/10.1002/hipo.23074>

Cohen, M. X. (2014). *Analyzing Neural Time Series Data: Theory and Practice*. The MIT Press. <https://doi.org/10.7551/mitpress/9609.001.0001>

De Gardelle, V., Waszczuk, M., Egner, T., & Summerfield, C. (2013). Concurrent Repetition Enhancement and Suppression Responses in Extrastriate Visual Cortex. *Cerebral Cortex*, 23(9), 2235–2244. <https://doi.org/10.1093/cercor/bhs211>

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, 134(1), 9–21. <https://doi.org/10.1016/j.jneumeth.2003.10.009>

Dolcos, F., Miller, B., Kragel, P., Jha, A., & McCarthy, G. (2007). Regional brain differences in the effect of distraction during the delay interval of a working memory task. *Brain Research*, 1152, 171–181. <https://doi.org/10.1016/j.brainres.2007.03.059>

DuBrow, S., & Davachi, L. (2013). The influence of context boundaries on memory for the sequential order of events. *Journal of Experimental Psychology: General*, 142(4), 1277–1286. <https://doi.org/10.1037/a0034024>

DuBrow, S., & Davachi, L. (2014). Temporal Memory Is Shaped by Encoding Stability and Intervening Item Reactivation. *The Journal of Neuroscience*, 34(42), 13998–14005. <https://doi.org/10.1523/JNEUROSCI.2535-14.2014>

DuBrow, S., & Davachi, L. (2016). Temporal binding within and across events. *Neurobiology of Learning and Memory*, 134 Pt A, 107–114. <https://doi.org/10.1016/j.nlm.2016.07.011>

Egner, T., Monti, J. M., & Summerfield, C. (2010). Expectation and Surprise Determine Neural Population Responses in the Ventral Visual Stream. *The Journal of Neuroscience*, 30(49), 16601–16608. <https://doi.org/10.1523/JNEUROSCI.2770-10.2010>

Ezzyat, Y., & Davachi, L. (2011). What Constitutes an Episode in Episodic Memory? *Psychological Science*, 22(2), 243–252. <https://doi.org/10.1177/0956797610393742>

Fukuda, K., Mance, I., & Vogel, E. K. (2015). a Power Modulation and Event-Related Slow Wave Provide Dissociable Correlates of Visual Working Memory. *Journal of Neuroscience*, 35(41), 14009–14016. <https://doi.org/10.1523/JNEUROSCI.5003-14.2015>

Fukuda, K., & Woodman, G. F. (2017). Visual working memory buffers information retrieved from visual long-term memory. *PNAS Proceedings of the National Academy of Sciences of the United States of America*, 114(20), 5306–5311. <https://doi.org/10.1073/pnas.1617874114>

Güler, B., Adıgüzel, Z., Uysal, B., & Günseli, E. (2024). Discrete memories of a continuous world: A working memory perspective on event segmentation. *Current Research in Behavioral Sciences*, 6, 100145. <https://doi.org/10.1016/j.crbeha.2023.100145>

Güler, B., Serin, F., & Günseli, E. (2025). Prediction error is out of context: The dominance of contextual stability in structuring episodic memories. *Psychonomic Bulletin & Review*. <https://doi.org/10.3758/s13423-025-02723-4>

Günseli, E., Fahrenfort, J. J., van Moorselaar, D., Daoultzis, K. C., Meeter, M., & Olivers, C. N. L. (2019). EEG dynamics reveal a dissociation between storage and selective attention within working memory. *Scientific Reports*, 9(1), Article 1. <https://doi.org/10.1038/s41598-019-49577-0>

Hahamy, A., Dubossarsky, H., & Behrens, T. E. J. (2023). The human brain reactivates context-specific past information at event boundaries of naturalistic experiences. *Nature Neuroscience*, 26(6), 1080–1089. <https://doi.org/10.1038/s41593-023-01331-6>

Hakim, N., Adam, K. C. S., Gunseli, E., Awh, E., & Vogel, E. K. (2019). Dissecting the Neural Focus of Attention Reveals Distinct Processes for Spatial Attention and Object-Based Storage in Visual Working Memory. *Psychological Science*, 30(4), 526–540. <https://doi.org/10.1177/0956797619830384>

Heinz, A. J., & Johnson, J. S. (2017). Load-Dependent Increases in Delay-Period Alpha-Band Power Track the Gating of Task-Irrelevant Inputs to Working Memory. *Frontiers in Human Neuroscience*, 11, 250. <https://doi.org/10.3389/fnhum.2017.00250>

Heusser, A. C., Ezzyat, Y., Shiff, I., & Davachi, L. (2018). Perceptual boundaries cause mnemonic trade-offs between local boundary processing and across-trial associative

binding. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 44(7), 1075–1090. <https://doi.org/10.1037/xlm0000503>

Hu, Z., Barkley, C. M., Marino, S. E., Wang, C., Rajan, A., Bo, K., Samuel, I. B. H., & Ding, M. (2019). Working Memory Capacity Is Negatively Associated with Memory Load Modulation of Alpha Oscillations in Retention of Verbal Working Memory. *Journal of Cognitive Neuroscience*, 31(12), 1933–1945. [https://doi.org/10.1162/jocn\\_a\\_01461](https://doi.org/10.1162/jocn_a_01461)

Ikkai, A., McCollough, A. W., & Vogel, E. K. (2010). Contralateral Delay Activity Provides a Neural Measure of the Number of Representations in Visual Working Memory. *Journal of Neurophysiology*, 103(4), 1963–1968. <https://doi.org/10.1152/jn.00978.2009>

Jafarpour, A., Buffalo, E. A., Knight, R. T., & Collins, A. G. E. (2022). Event segmentation reveals working memory forgetting rate. *iScience*, 25(3), 103902. <https://doi.org/10.1016/j.isci.2022.103902>

Kleiner, M., Brainard, D., Pelli, D., Ingling, A., Murray, R., & Broussard, C. (2007). What's new in psychtoolbox-3. *Perception*, 36(14), 1–16.

Konkle, T., Brady, T. F., Alvarez, G. A., & Oliva, A. (2010). Conceptual Distinctiveness Supports Detailed Visual Long-Term Memory for Real-World Objects. *Journal of Experimental Psychology: General*, 139(3), 558–578. <https://doi.org/10.1037/a0019165>

Konkle, T., & Caramazza, A. (2013). Tripartite organization of the ventral stream by animacy and object size. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, 33(25), 10235–10242. <https://doi.org/10.1523/JNEUROSCI.0983-13.2013>

Konkle, T., & Oliva, A. (2012). A familiar-size Stroop effect: Real-world size is an automatic property of object representation. *Journal of Experimental Psychology: Human Perception and Performance*, 38(3), 561–569. <https://doi.org/10.1037/a0028294>

Kumar, S., Higgs, S., Rutters, F., & Humphreys, G. W. (2016). Biased towards food: Electrophysiological evidence for biased attention to food stimuli. *Brain and Cognition*, 110, 85–93. <https://doi.org/10.1016/j.bandc.2016.04.007>

Kurby, C. A., & Zacks, J. M. (2008). Segmentation in the perception and memory of events. *Trends in Cognitive Sciences*, 12(2), 72–79. <https://doi.org/10.1016/j.tics.2007.11.004>

Lawrence, Z., & Peterson, D. (2016). Mentally walking through doorways causes forgetting: The location updating effect and imagination. *Memory*, 24(1), 12–20. <https://doi.org/10.1080/09658211.2014.980429>

Leroy, N., Majerus, S., & D'Argembeau, A. (2024). Working memory capacity for continuous events: The root of temporal compression in episodic memory? *Cognition*, 247, 105789. <https://doi.org/10.1016/j.cognition.2024.105789>

Leroy, N., Majerus, S., & D'Argembeau, A. (2025). The role of working memory in encoding the temporal structure of events in episodic memory: Evidence from a dual-task paradigm. *Memory & Cognition*. <https://doi.org/10.3758/s13421-025-01798-7>

Liu, Y., Dolan, R. J., Kurth-Nelson, Z., & Behrens, T. E. J. (2019). Human Replay Spontaneously Reorganizes Experience. *Cell*, 178(3), 640-652.e14. <https://doi.org/10.1016/j.cell.2019.06.012>

Lopez-Calderon, J., & Luck, S. J. (2014). ERPLAB: An open-source toolbox for the analysis of event-related potentials. *Frontiers in Human Neuroscience*, 8, 213. <https://doi.org/10.3389/fnhum.2014.00213>

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, 390(6657), 279–281. <https://doi.org/10.1038/36846>

McArthur, G., Budd, T., & Michie, P. (1999). The attentional blink and P300. *NeuroReport*, 10(17), 3691.

Ongchoco, J. D. K., & Scholl, B. J. (2019). Did that just happen? Event segmentation influences enumeration and working memory for simple overlapping visual events. *Cognition*, 187, 188–197. <https://doi.org/10.1016/j.cognition.2019.01.002>

Pettijohn, K. A., & Radvansky, G. A. (2016). Narrative event boundaries, reading times, and expectation. *Memory & Cognition*, 44(7), 1064–1075.

Rademaker, R. L., Bloem, I. M., De Weerd, P., & Sack, A. T. (2015). The impact of interference on short-term memory for visual orientation. *Journal of Experimental Psychology: Human Perception and Performance*, 41(6), 1650–1665. <https://doi.org/10.1037/xhp0000110>

Radvansky, G. A., & Copeland, D. E. (2006). Walking through doorways causes forgetting: Situation models and experienced space. *Memory & Cognition*, 34(5), 1150–1156. <https://doi.org/10.3758/bf03193261>

Radvansky, G. A., Krawietz, S. A., & Tamplin, A. K. (2011). Walking through doorways causes forgetting: Further explorations. *Quarterly Journal of Experimental Psychology* (2006), 64(8), 1632–1645. <https://doi.org/10.1080/17470218.2011.571267>

Radvansky, G. A., Tamplin, A. K., & Krawietz, S. A. (2010). Walking through doorways causes forgetting: Environmental integration. *Psychonomic Bulletin & Review*, 17(6), 900–904. <https://doi.org/10.3758/PBR.17.6.900>

Radvansky, G. A., & Zacks, J. M. (2017). Event boundaries in memory and cognition. *Current Opinion in Behavioral Sciences*, 17, 133–140. <https://doi.org/10.1016/j.cobeha.2017.08.006>

Schlichting, M. L., & Preston, A. R. (2016). Hippocampal–medial prefrontal circuit supports memory updating during learning and post-encoding rest. *Neurobiology of Learning and Memory*, 134, 91–106. <https://doi.org/10.1016/j.nlm.2015.11.005>

Schönbrodt, F. D., & Wagenmakers, E.-J. (2018). Bayes factor design analysis: Planning for compelling evidence. *Psychonomic Bulletin & Review*, 25(1), 128–142. <https://doi.org/10.3758/s13423-017-1230-y>

Shim, S., Mugisho, F. B., Davachi, L., & Baldassano, C. (2024). *Generating event boundaries in memory without prediction error*. <https://doi.org/10.31234/osf.io/4bdp6>

Silva, M., Baldassano, C., & Fuentemilla, L. (2019). Rapid Memory Reactivation at Movie Event Boundaries Promotes Episodic Encoding. *Journal of Neuroscience*, 39(43), 8538–8548. <https://doi.org/10.1523/JNEUROSCI.0360-19.2019>

Sols, I., DuBrow, S., Davachi, L., & Fuentemilla, L. (2017). Event Boundaries Trigger Rapid Memory Reinstatement of the Prior Events to Promote Their Representation in Long-Term Memory. *Current Biology*, 27(22), 3499–3504.e4. <https://doi.org/10.1016/j.cub.2017.09.057>

Speer, N. K., Zacks, J. M., & Reynolds, J. R. (2007). Human Brain Activity Time-Locked to Narrative Event Boundaries. *Psychological Science*, 18(5), 449–455. <https://doi.org/10.1111/j.1467-9280.2007.01920.x>

Summerfield, C., & De Lange, F. P. (2014). Expectation in perceptual decision making: Neural and computational mechanisms. *Nature Reviews Neuroscience*, 15(11), 745–756. <https://doi.org/10.1038/nrn3838>

Swallow, K. M., Zacks, J. M., & Abrams, R. A. (2009). Event boundaries in perception affect memory encoding and updating. *Journal of Experimental Psychology: General*, 138(2), 236–257. <https://doi.org/10.1037/a0015631>

Tombu, M., & Seiffert, A. E. (2008). Attentional costs in multiple-object tracking. *Cognition*, 108(1), 1–25. <https://doi.org/10.1016/j.cognition.2007.12.014>

van de Ven, V., Jäckels, M., & De Weerd, P. (2021). Time changes: Timing contexts support event segmentation in associative memory. *Psychonomic Bulletin & Review*. <https://doi.org/10.3758/s13423-021-02000-0>

van Moorselaar, D., Gunseli, E., Theeuwes, J., & N. L. Olivers, C. (2015). The time course of protecting a visual memory representation from perceptual interference. *Frontiers in Human Neuroscience*, 8. <https://doi.org/10.3389/fnhum.2014.01053>

Vogel, E. K., & Machizawa, M. G. (2004). Neural activity predicts individual differences in visual working memory capacity. *Nature*, 428(6984), 748–751. <https://doi.org/10.1038/nature02447>

Vogel, E. K., McCollough, A. W., & Machizawa, M. G. (2005). Neural measures reveal individual differences in controlling access to working memory. *Nature*, 438(7067), 500–503. <https://doi.org/10.1038/nature04171>

Walsh, K. S., McGovern, D. P., Clark, A., & O'Connell, R. G. (2020). Evaluating the neurophysiological evidence for predictive processing as a model of perception. *Annals of the New York Academy of Sciences*, 1464(1), 242–268. <https://doi.org/10.1111/nyas.14321>

Wu, X., Packard, P. A., García-Arch, J., Bunzeck, N., & Fuentemilla, L. (2023). Contextual incongruity triggers memory reinstatement and the disruption of neural stability. *NeuroImage*, 273, 120114. <https://doi.org/10.1016/j.neuroimage.2023.120114>

Zacks, J. M. (2020). Event Perception and Memory. *Annual Review of Psychology*, 71(1), 165–191. <https://doi.org/10.1146/annurev-psych-010419-051101>

Zacks, J. M., Speer, N. K., Swallow, K. M., Braver, T. S., & Reynolds, J. R. (2007). Event perception: A mind-brain perspective. *Psychological Bulletin*, 133(2), 273–293. <https://doi.org/10.1037/0033-2909.133.2.273>

Zhao, C., Vogel, E., & Awh, E. (2023). Change localization: A highly reliable and sensitive measure of capacity in visual working memory. *Attention, Perception & Psychophysics*, 85(5), 1681–1694. <https://doi.org/10.3758/s13414-022-02586-0>